RESEARCH PLAN PROPOSAL

Deep Learning based Approach for filling gaps in Remote Sensing Data

For registration to the degree of

Doctor of Philosophy

IN THE FACULTY OF COMPUTER SCIENCES & IT

THE IIS UNIVERSITY, JAIPUR

Submitted By
Ms. Jaya Saxena
Enrollment No: ICG/2018/26574

Under the Supervision of
Dr. Anubha Jain
HoD, Faculty of Computer Science & IT

Co-Supervisor
Dr. P Radha Krishna
Professor, NIT Warangal

Department of Computer Science & IT

July 2019

Table of Contents

1. TOPIC **3**

2. INTRODUCTION **3**

3. REVIEW OF LITERATURE **4**

3.1. METHODOLOGY OF LITERATURE REVIEW: **4**

3.2 REVIEWED ARTICLES **5**

3.2.1 Research Articles by year of publication: 5
3.2.2 Research article by Journal of Publication: 5
3.2.3 Research article by Status: 7
3.2.4 Citation Analysis: 7
3.3 Reviewed Literature 10
3.4 A Brief summary of Reviewed Literature 42

4. MOTIVATION/JUSTIFICATION AND RELEVANCE **46**

- Savitzky–Golayfilter: 46
- Fourier analysis: 46
- Wavelet transform: 46
- Curve Fitting: 47

4.2 COMPARISON OF THE METHODS **48**

4.3 DEEP LEARNING & ITS APPLICABILITY TO REMOTE SENSING AREA **50**

4.4 METHODOLOGY IN DEEP LEARNING **50**

5. OBJECTIVES **51**

6. HYPOTHESES **51**

7. PLAN OF WORK AND METHODOLOGY **52**

7.1 RESEARCH DESIGN **52**

7.2 DATA COLLECTION **52**

7.3 UNIVERSE AND SAMPLE OF THE STUDY **53**

7.4 TOOLS AND TECHNIQUES **53**

8. PLACE OF WORK AND FACILITIES AVAILABLE **53**

9 LIMITATIONS **53**

10 REFERENCES **53**

1.Topic

"Deep Learning based Approach for filling gaps in Remote Sensing Data".

2. Introduction

Remote sensing is the technology of acquiring information about the Earth's surface (land and ocean) and atmosphere using sensors onboard airborne(aircraft, balloons) or spaceborne(satellites, space shuttles) platforms. The era of satellite remote sensing was open in the 1960s when cameras and electronic sensors were mounted on spacecraft. Nowadays there is a big assortment of satellite systems actively recording information about the Earth. A wide variety of imagery is available from satellites. Both active and passive sensors, operating from the microwave to the ultraviolet regions of the electromagnetic spectrum collect a large amount of information about the earth's surface every day. Each of the systems varies in terms of their spatial, spectral, radiometric and temporal resolution. Those characteristics play an important role in defining which applications the sensor is best suited for. The main benefits of satellite remote sensing are following:

- The data are available for large areas: for example: 35 000km^{2}for LANDSAT scene, 3 600 km^{2}for SPOT scene.
- They are available on a regular basis for all points on the globe (repetitive coverage): data may be acquired every 1-3 days (16 days in the case of LANDSAT, 1-3 days in the case of SPOT).
- They are objective: the sensor-transmission-reception system involves no human intervention.
- To collect data, the sensors use the wide spectrum of electromagnetic spectrum (EMS) and use several band (areas of the EMS) at once (LANDSAT TM 7, hyper-spectral: from tens to hundreds of spectral bands)
- They are in digital form and geometrically corrected images can be used to provide a base to overlay other data or to be used as part of an analysis in a GIS environment

However, many time data sets derived from optical satellite sensors partially show clouds instead of the Earth's surface. Further, several times the data may be of low quality due to technical glitches and get a miss for some unavoidable human errors or due to environmental factors.

Several attempts were made to bridge the missing data. Number of satellite-derived time series reconstruction methods have been developed, for instance, the Savitzky–Golay filter [Chen, J.*et.al.* 2004], the Fourier analysis [Moody, A.; Johnson, D.M. (2001)], the wavelet transform[Qiu, B.*et. al*. 2016], and function fitting[Jonsson, P. *et. al*. 2002].

It is observed that they may not perform well with less high-quality observations and are limited by insufficient temporal information. Also, these traditional methods do not provide similar outputs for different terrains and for spatial and temporal domains.

This provide requirement to explore in new direction. Since remote sensing data sets are widely available and are continuously obtained, a data centric approach as compared to task centric will be more applicable and useful.

Artificial neural networks, machine learning and deep learning are upcoming technologies which are data centric and have proved their utility in many domains.

After the **Hinton's revolutionary work in 2006** on Deep Belief Networks (DBNs) and subsequently works had change the outlook of the subject with following key principles: (a) Unsupervised learning of representations is used to pre-train each layer. (b) Unsupervised training of one layer at a time, on top of the previously trained ones. Enabling the representation learned at each level is the input for the next layer. (c) Use supervised training to fine-tune all the layers. These features facilitate automatic learning at multiple levels of abstraction, allowing a system to learn complex functions mapping of the input to the output directly from data, without depending completely on human-crafted features. This is especially important for higher-level abstractions, which humans often do not know how to specify explicitly in terms of raw sensory input. The ability to automatically learn powerful features is becoming increasingly important as the amount of data and range of applications to machine learning methods continues to grow. Where other methods have worked on Spatial, Temporal or Spatio-Temporal domain, deep learning methods are applied on all these three domains simultaneously.

This has motivated to explore Deep Learning technology in bridging the gaps for missing remote sensing data sets.

3. Review of Literature

3.1. Methodology of Literature Review:

A literature review includes the current knowledge including substantive findings, as well as theoretical and methodological contributions to a particular topic. Literature reviews are secondary sources, and do not report new or original experimental work. Most often associated with academic-oriented literature, such reviews are found in academic journals, and are not to be confused with book reviews that may also appear in the same publication. Literature reviews are a basis for research in nearly every academic field.

The study has used **Systematic Literature Review** methodology and presented below.

1. **Literature collection and boundary identification:**
   - Database used, Google scholar for searching articles;
   - Paper published only in peer-reviewed academic journals are considered;
   - Paper are collected for last 20 years ; and
   - Paper with full text available is considered most of the time.
2. **Description and Classification of Literature:**
   - Analysis by year of publication
   - Analysis by research methods :
     Empirical
     Conceptual
     Survey
   - Analysis by Journal of Publications
   - Analysis by Status :
     National
     International

3.2 Reviewed Articles

3.2.1Research Articles by year of publication:

Year	No. of Research Paper
1994-2000	5
2001-2005	3
2006-2010	7
2011-2015	16
2016-2018	9
2019	1

3.2.2 Research article by Journal of Publication:

S.No.	Journal of Publication
1	Remote Sensing of Environment
2	IEEE Transactions on Geoscience and Remote Sensing
3	International Journal of Remote Sensing
4	Remote Sensing
5	IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing
6	PLoS (Public Library of Science) ONE
7	Computers & Geosciences
8	Journal of Atmospheric and Oceanic Technology
9	ISPRS Journal of Photogrammetry and Remote Sensing
10	Oceans-St. John's
11	IEEE International Geoscience and Remote Sensing Symposium (IGARSS)
12	Journal of Statistical Planning and Inference
13	Technical report,McGill University and Microsoft Maluuba,
14	IEEE Access
15	SIAM Review
16	44th Euromicro Conference on Software Engineering and Advanced Applications
17	Neural Networks
18	MIT Press
19	Computer Science
20	SIAM Review
21	Indian Society of Remote Sensing

3.2.3 Research article by Status:

National	International
01	40

3.2.4 Citation Analysis:

Citation means that someone has referred work of other author(s). In the present literature review, citation information provided by Google Scholar has been used for citation analysis to observe the quality of papers.

S.NO	Author	No. of citations
1	J. Verbesselt, R. Hyndman, G. Newnham, and D. Culvenor	681
2	J. Verbesselt, R. Hyndman, A. Zeileis, and D. Culvenor	346
3	A. Verger, F. Baret, M. Weiss, S. Kandasamy, and E. Vermote	41
4	S. Jamali, P. Jönsson, L. Eklundh, J. Ardö, and J. Seaquist	76
5	G. J. Roerink, M. Menenti, and W. Verhoef	510
6	Á. Moreno, F. J. García-Haro, B. Martínez, and M. A. Gilabert	20
7	A. Verger, F. Baret, and M. Weiss	15
8	M. Neteler	177
9	J. P. W. Scharlemann*et al.*	210
10	P. Jönsson and L. Eklundh	1242
11	J. Chen, P. Jönsson, M. Tamura, Z. Gu, B. Matsushita, and L. Eklundh	1150
12	R. R. Colditz, C. Conrad, T. Wehrmann, M. Schmidt, and S. Dech	101
13	Y. Zhu, E. L. Kang, Y. Bo, Q. Tang, J. Cheng, and	3

	Y. He	
14	E. A. Addink	46
15	R. E. Rossi, J. L. Dungan, and L. R. Beck	134
16	J. Chen, X. Zhu, J. E. Vogelmann, F. Gao, and S. Jin	260
17	X. Zhu, D. Liu, and J. Chen	96
18	J. M. Beckers and M. Rixen	320
19	L. Poggio, A. Gimona, and I. Brown	39
20	D. J. Weiss, P. M. Atkinson, S. Bhatt, B. Mappin, S. I. Hayand P. W. Gething	57
21	R. Lguensat, P. Tandeo, R. Fablet, and R. Garello	8
22	J. C. de Oliveira, J. C. N. Epiphanio, and C. D. Rennó	13
23	J. C. de Oliveira and J. C. N. Epiphanio	3
24	N. Golyandina and E. Osipov	125
25	L. Guo, L. Lei, Z. C. Zeng, P. Zou, D. Liu, and B. Zhang	9
26	Z. Zeng, L. Lei, S. Hou, F. Ru, X. Guan, and B. Zhang	15
27	Qiang Zhang , Qiangqiang Yuan, Chao Zeng , Xinghua Li, andYancong W	7
28	Michael Kwok-Po Ng, Qiangqiang Yuan, Li Yan, Jing Sun	12
29	Peter Henderson, Riashat Islam, Philip BachmanJoelle Pineau, DoinaPrecup, David Meger	136
30	Alexandra L'Heureux, Katarina Grolinger, Hany F. Elyamany& Miriam A. M. Capretz	64
31	Leon Bottou, Frank E. Curtisy, Jorge Nocedalz	345
32	Anders Arpteg, BjörnBrinne, Jan Bosch, Luka Crnkovic-Friis	54

33	James Gerard Wolff	24
34	JuergenSchmidhuber	5977
35	Hornik. K; Stinchcombe, M; White,H	16988
36	Simard, P; Bottou, L; Haffner,P; LeCun,Y.	164
37	SutskeverIlya, I; Martens, J; Hinton, G.	851
38	Schmidt, U; Roth, S.	223
39	Ulyanov, D;Vedaldi, A; Lempitsky, V.	204
40	Bengio Y	3850

3.3Reviewed Literature

Study Literature	Title of the paper	Published in	Study objective/ Study Description	Observation
Verbesselt, J., Hyndman, R., Newnham, G., Culvenor, D.	Detecting trend and seasonal changes in satellite image time series	*Remote Sens.Environ.* vol. 114 no. 1 pp. 106–115 2010.	A wealth of remotely sensed image time series covering large areas is now available to the earth science community. Change detection methods are often not capable of detecting land coverchanges within time series that are heavily influenced by seasonal climatic variations. Detecting change within the trend and seasonal components of time series enables the classification ofdifferent types of changes. Changes occurring in the trend component often indicate disturbances (e.g. fires, insect attacks), while changes occurring in the seasonal component indicatephenological changes (e.g. change in land cover type). A generic change detection approach is proposed for time series by detecting and characterizing Breaks For Additive	It revealed that BFAST can robustly detect change with different magnitudes(> 0.1 NDVI) within time series with different noise levels (0.01–0.07 σ) and seasonal amplitudes (0.1–0.5 NDVI). This work showed that BFAST is able to detect and characterize spatial and temporal changes in aforested landscape. BFAST is not specific to a particular data type and can be applied to time series without the need to normalize for land cover types, select a reference period, or changetrajectory. The method can be integrated within monitoring frameworks and used as an alarm system to flag when and where changes occur.

			Seasonal and Trend(BFAST). BFAST integrates the decomposition of time series into trend, seasonal, and remainder components with methods for detecting change within time series. BFAST iteratively estimatesthe time and number of changes, and characterizes change by its magnitude and direction. Tested BFAST by simulating 16-day Normalized Difference Vegetation Index (NDVI) time serieswith varying amounts of seasonality and noise, and by adding abrupt changes at different times and magnitudes. Additionally, BFAST was applied to 16-day NDVI Moderate Resolution ImagingSpectroradiometer (MODIS) composites for a forested study area in south eastern Australia.	
Verbesselt, J., Hyndman, R., Zeileis, A., Culvenor, D.	Phenological change detection while accounting for abrupt and gradual trends in satellite image time series	*Remote Sens. Environ.* vol. 114 no. 12 pp. 2970–2980 2010.	A challenge in phenology studies is to understand what constitutes phenological change amidst background variation. The majority of phenological studies have focused on extracting criticalpoints in the seasonal growth cycle, without exploiting the full temporal detail. The high degree of phenological variability between years	It demonstrates the phenological change detection ability of a method for detecting change within time series. BFAST, Breaks For Additive Seasonal and Trend, integrates the decomposition of time series into trend, seasonal, and remainder components with

			demonstrates the necessity of distinguishing long-termphenological change from temporal variability.Between different land cover types the seasonal amplitude varies and determines the signal-to-noise ratio, and as such the capacity to differentiatephenological changes from noise. Application of the method on 16-day NDVI MODIS images from 2000 until 2009 for a forested study area in south eastern Australia confirmed these results. The method is globally applicable since it analyzes each pixel individually without the setting ofthresholds to detect change within a time series. Long-term phenological changes can be detected within NDVI time series of a large range of land cover types (e.g. grassland, woodlands anddeciduous forests) having a seasonal amplitude larger than the noise level. The method can be applied to any time series data and it is not necessarily limited to NDVI.	methods for detecting change. They have tested BFAST by simulating 16-day NDVI time series with varying amounts of seasonal amplitude and noise, containing abrupt disturbances (e.g. fires) and long-term phenological changes. This revealed that the method is able todetect the timing of phenological changes within time series while accounting for abrupt disturbances and noise. Results showed that the phenological change detection is influenced by thesignal-to-noise ratio of the time series.
Verger, A.;	The CACAO method for smoothing	*IEEE Trans. Geosci. Remote Sens.*	Consistent, continuous, and long time series of global biophysical variables	The resulting smoothedtime series captures well the

Baret, F.; Weiss, M.; Kandasamy, S.; Vermote, E.	gap fillingand characterizing seasonal anomalies in satellite time series	vol. 51 no. 4 pp. 1963–1972 Apr. 2013.	derived from satellite data arerequired for global change research. A novel climatology fitting approach called CACAO (ConsistentAdjustment of the Climatology to Actual Observations) is proposed to reduce noise and fill gaps in time seriesby scaling and shifting the seasonal climatological patterns to the actual observations. The shift and scaleCACAO parameters adjusted for each season allow quantifying shifts in the timing of seasonal phenology andinter-annual variations in magnitude as compared to the average climatology. CACAO was assessed firstover simulated daily Leaf Area Index (LAI) time series with varying fractions of missing data and noise. Then,performances were analyzed over actual satellite LAI products derived from AVHRR Long-Term Data Recordfor the 1981-2000 period over the BELMANIP2 globally representative sample of sites. Comparison with twowidely used temporal filtering methods-the asymmetric Gaussian (AG) model and the Savitzky-Golay (SG)filter as implemented in TIMESAT-revealed	vegetation dynamics and shows no gaps as compared to the 50-60% of stillmissing data after AG or SG reconstructions.Results of simulation experiments as well as confrontation withactual AVHRR time series indicate that the proposed CACAO method is more robust to noiseand missing data than AG and SG methods for phenology extraction.

			that CACAO achieved better performances for smoothing AVHRRtime series characterized by high level of noise and frequent missing observations.	
Jamali, S.; Jönsson, P.; Eklundh, L.; Ardö, J.; Seaquist, J.	Detecting changes in vegetation trends using time series segmentation	*Remote Sens. Environ.* vol. 156 pp. 182–195 Jan. 2015.	Although satellite-based sensors have made vegetation data series available for several decades, the detection of vegetation trend and change is not yet straightforward. This is partly due to thescarcity of available change detection algorithms suitable for identifying and characterizing both abrupt and non-abrupt changes, without sacrificing accuracy or computational speed. It proposes a user-friendly program for analyzing vegetation time series, with two main application domains: generalizing vegetation trends to main features, and characterizing vegetation trend changes.Detecting Breakpoints and Estimating Segments in Trend (DBEST) was tested and evaluated using simulated NormalizedDifference Vegetation Index (NDVI) data at two sites, which included different types of changes. Evaluation results	This program, Detecting Breakpoints and Estimating Segments in Trend (DBEST) uses a novel segmentation algorithm which simplifies the trend into linear segments using one of three userdefinedparameters: a generalization-threshold parameter δ, the m largest changes, or a threshold β for the magnitude of changes of interest for detection. The outputs of DBEST are thesimplified trend, the change type (abrupt or non-abrupt), and estimates for the characteristics (time and magnitude) of the change. We observed that DBEST is able to detect and characterize changes over large areas and that DBEST is a fast, accurate and flexible tool for trenddetection, and is

			demonstrate that DBEST quickly and robustly detects both abrupt and nonabruptchanges, and accurately estimates change time and magnitude.DBEST was also tested using data from the Global Inventory Modeling and Mapping Studies (GIMMS) NDVI image time series for Iraq for the period 1982–2006, and was able to detect andquantify major change over the area.	applicable to global change studies using time series of remotely sensed data sets.
Chen, J.; Jonsson, P.; Tamura, M.; Gu, Z.H.; Matsushita, B.; Eklundh, L.	A simple method for reconstructing a high-quality NDVI time-series data set based on the Savitzky–Golay filter	*Remote Sens. Environ.* vol. 91 nos. 3–4 pp. 332–344 2004.	Although the Normalized Difference Vegetation Index (NDVI) time-series data, derived from NOAA/AVHRR, SPOT/VEGETATION, TERRA or AQUA/MODIS, has been successfully used inresearch regarding global environmental change, residual noise in the NDVI time-series data, even after applying strict pre-processing, impedes further analysis and risks generating erroneousresults. Based on the assumptions that NDVI time-series follow annual cycles of growth and decline of vegetation, and that clouds or poor atmospheric conditions usually depress NDVI values,we have developed in the present study a simple	This method was developed to make data approach the upper NDVI envelope and to reflect the changes in NDVI patterns via an iteration process. From the results obtained by applying the developed method to a 10-day MVC SPOT VGT-S product, it provide optimized parameters for the new method and compare this technique with the BISE algorithm and Fourier-based fitting method. The results indicate that the new method is more effective in obtaining high-quality NDVI time-series.

			but robust method based on the Savitzky–Golay filter to smooth out noise in NDVI time-series, specifically that caused primarily by cloudcontamination and atmospheric variability.	
Moreno, A.; García-Haro, F. J.; Martínez, B.; Gilabert, M.A.	Noise reduction and gap filling of fAPAR time series using an adapted local regression filter	*Remote Sens.* vol. 6 no. 9 pp. 8238–8260 2014.	Time series of remotely sensed data are an important source of information forunderstanding land cover dynamics. In particular, the fraction of absorbed photosyntheticactive radiation (fAPAR) is a key variable in the assessment of vegetation primaryproduction over time. However, the fAPAR series derived from polar orbit satellites arenot continuous and consistent in space and time. Filtering methods are thus required to fillin gaps and produce high-quality time series. This study proposes an adapted (iterativelyreweighted) local regression filter (LOESS) and performs a benchmarking intercomparisonwith four popular and generally applicable smoothing methods: Double Logistic (DLOG), smoothing spline (SSP), Interpolation for Data Reconstruction	The results have shown that ASG and the adapted LOESS performbetter in recovering fAPAR time series over multiple controlled noisy scenarios. Bothmethods can robustly reconstruct the fAPAR trajectories, reducing the noise up to 80% inthe worst simulation scenario, which might be attributed to the quality control (QC)MODIS information incorporated into these filtering algorithms, their flexibility andadaptation to the upper envelope. The adapted LOESS is particularly resistant to outliers.This method clearly outperforms the other considered methods to deal with the highpresence of gaps and noise in satellite data records. The low

			(IDR) and adaptiveSavitzky-Golay (ASG). This paper evaluates the main advantages and drawbacks of theconsidered techniques. The LOESS approach is recommended in most remotesensing applications, such as gap-filling, cloud-replacement, and observing temporaldynamics in situ where rapid seasonal changes are produced.	RMSE and biases obtainedwith the LOESS method (|rMBE| < 8%; rRMSE< 20%) reveals an optimal reconstructioneven in most extreme situations with long seasonal gaps.
Verger, A., Baret, F., Weiss, M.	Near real-time vegetation monitoring at global scale	*IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens.* vol. 7 no. 8 pp. 3473–3481 Aug. 2014.	The NRT algorithm for near-real time estimation of global LAI, FAPAR, and FCOVER variables from SPOT/VEGETATION (VGT) satellite data is described here. It consists of three steps: 1) neural networks (NNT) (one for each variable) to provide instantaneous estimates from daily VGT-P reflectances; 2) a multistep filtering approach to eliminate data mainly affected by atmospheric effects and snow cover; and 3) Savitzky-Golay and climatology temporal smoothing and gap filling techniques to ensure consistency and continuity as well as short-term projection of the product dynamics. Performances of NRT estimates were evaluated by comparing	The root-mean-square error (RMSE) between NRT and HIST LAI is lower than 0.4 in all cases. It shows a rapid exponential decay with the number of observations in the composition window with convergence when 30 observations are available. NRT products are in good agreement with ground data (RMSE of 0.69 for LAI, 0.09 for FAPAR, and 0.14 for FCOVER) and consistent with GEOV1/VGT products with a significant improvement in terms of continuity (only 1% of missing data) and smoothness, especially

			with other products over the 2005-2008 period: 1) the offline estimates from the application of the algorithm over historical time series (HIST); 2) the geoland2 version 1 products also issued from VGT (GEOV1/VGT); and 3) ground data. NRT rapidly converges closely to the HIST processing after six decades (10-day period) with major improvement after two decades.	at high latitudes, and Equatorial areas.
Neteler, M.,	Estimating daily land surface temperatures in mountainous environments by reconstructed MODIS LST data	*Remote Sens.* vol. 2 no. 1 pp. 333–351 2010.	Continuous monitoring of extreme environments, such as the European Alps, ishampered by the sparse and/or irregular distribution of meteorological stations, thedifficulties in performing ground surveys and the complexity of interpolating existingstation data. Remotely sensed Land Surface Temperature (LST) is therefore of majorinterest for a variety of environmental and ecological applications. But while MODIS LSTdata from the Terra and Aqua satellites are aimed at closing the gap between data demandand availability, clouds and other atmospheric disturbances often obscure parts or even theentirety of these satellite	A novel algorithm is presented in this paper, which is ableto reconstruct incomplete MODIS LST maps. All nine years of the available daily LST data(2000–2008) have been processed, allowing the original LST map resolution of 1,000 m tobe improved to 200 m, which means the resulting LST maps can be applied at a regionallevel. Extracted time series and aggregated data are shown as examples and are compared tometeorological station time series as an indication of the quality obtained.

			images.	
Scharleman, J. P. W., n*et al.*	Global data for ecology and epidemiology: A novel algorithm for temporal Fourier processing MODIS data	*PLoS ONE* vol. 3 no. 1 p. e1408 2008.	Remotely-sensed environmental data from earth-orbiting satellites are increasingly used to model thedistribution and abundance of both plant and animal species, especially those of economic or conservation importance. Timeseries of data from the MODerate-resolution Imaging Spectroradiometer (MODIS) sensors on-board NASA's Terra and Aquasatellites offer the potential to capture environmental thermal and vegetation seasonality, through temporal Fourier analysis,more accurately than was previously possible using the NOAA Advanced Very High Resolution Radiometer (AVHRR) sensordata. MODIS data are composited over 8- or 16-day time intervals that pose unique problems for temporal Fourier analysis.	We present a novel spline-based algorithm that overcomes theprocessing problems of composited MODIS data. The algorithm is tested on artificial data generated using randomly selectedvalues of both amplitudes and phases, and provides an accurate estimate of the input variables under all conditions. Thealgorithm was then applied to produce layers that capture the seasonality in MODIS data for the period from 2001 to 2005.Applying standard techniques to MODIS data can introduce errors of up to 30% in the estimation of the amplitudes and phasesof the Fourier harmonics. The finer spatial and temporal resolution, combined with the greater geolocational and spectral accuracy of the MODIS instruments, compared with previous multitemporaldata sets, mean that these data may be used with greater confidence in

				species' distribution modeling.
Jönsson, P.,Eklundh, L.	TIMESAT—A program for analyzing time-series of satellite sensor data	*Comput. Geosci.* vol. 30 no. 8 pp. 833–845 2004.	Time-series of vegetation index derived from satellite spectral measurements can be used togain information on seasonal vegetation development. This information an aid analyzes of thefunctional and structural characteristics of the global and regional land cover and adds to ourcurrent knowledge of global cycles of energy and matter. Long time-series of vegetation indexdata can also provide information on shifts in the spatial distribution of bio-climatic zones,indicating variations in large-scale circulation patterns or land-use changes.Although the value of remotely sensed time-series data for monitoring vegetation seasons hasbeen firmly established, only a limited number of methods for exploring and extracting seasonalityparameters from such data series exists. For this reason the TIMESAT programpackage for extracting seasonal parameters has been developed. The TIMESAT programis tested with the 8 km by 8 km pixel resolution Pathfinder	The program uses an adaptive Savitzky-Golay filtering method and newly developed methods based on upper envelope weighted fits to asymmetric Gaussian and double logistic model functions. From the fitted model functions a number of phonological parameters, e.g. beginning and end of the growing season, can be extracted.Being a completely general program TIMESAT can handle also other types of data such asmeteorological index and fire data

			AVHRR Land (PAL) data setgenerated by NASA/NOAA and the 250 m by 250 m pixel resolution Terra/MODIS data.	
Colditz, R. R., Conrad, C., Wehrmann, T., Schmidt, M., Dech, S.	TiSeG: A flexible software tool for time-series generation of MODIS data utilizing the quality assessment science data set	*IEEE Trans. Geosci. Remote Sens.* vol. 46 no. 10 pp. 3296–3308 Oct. 2008.	Time series generated from remotely sensed data are important for regional to global monitoring, estimating long-term trends, and analysis of variations due to droughts or other extreme events such as El Nintildeo. Temporal vegetation patterns including phenological states, photosynthetic activity, or biomass estimations are an essential input for climate modeling or the analysis of the carbon cycle. However, long-term analysis requires accurate calibration and error estimation, i.e., the quality of the time series determines its usefulness. Although previous attempts of quality assessment have been made with NOAA-AVHRR data, a first rigorous concept of data quality and validation was introduced with the MODIS sensors. According to user-defined settings, the tool visualizes the spatial and temporal data availability by generating two indices, the number of	This paper presents the time-series generator (TiSeG), which analyzes the pixel-level quality-assurance science data sets of all gridded MODIS land (MODLand) products suitable for time-series generation. This paper describes the functionality of TiSeG and shows an example of enhanced vegetation index time-series generation with numerous settings for Germany. The example indicates the improvements of time series when the quality information is employed with a critical weighting between data quality and the necessary quantity for meaningful interpolation.

			invalid pixels and the maximum gap length. Quality settings can be modified spatially and temporally to account for regional and seasonal variations of data quality. The user compares several quality settings and masks or interpolates the data gaps.	
Zhu, Y., Kang, E. L., Bo, Y., Tang, Q., Cheng, J., He, Y.	A robust fixed rank Kriging method for improving the spatial completeness and accuracy of satellite SST products	*IEEE Trans. Geosci. Remote Sens.* vol. 53 no. 9 pp. 5021–5035 Sep. 2015.	Sea surface temperature (SST) plays a vital role in the Earth's atmosphere and climate systems. Complete and accurate SST observations are in great demand for forecasting tropical cyclones and projecting climate change. Satellite remote sensing has been used to retrieve SST globally, but missing values and biased observations impose difficulties on practical applications of these satellite-derived SST data. Conventional spatial statistics methods such as kriging have been widely used to fill the gaps. However, when such conventional methods are used to analyze a massive satellite data set of size n, the inversion of the n × n covariance matrix may require O(n 3) computations, which make the computation very intensive or even infeasible. The fixed rank kriging	This paper construct a data-driven bias-correction model for the correction of the bias in satellite SSTs and develop a robust FRK (R-FRK) method so that the dimension reduction can be used to the satellite data in irregular regions with missing data. It implements the bias-correction model and the R-FRK to the level-3 mapped night Moderate Resolution Imaging Spectroradiometer SSTs. The accuracy of the resulting predictions is assessed using the co-located drifting buoy SST observations, in terms of mean bias (bias), root-mean-squared error, and R squared (R 2). The spatial completeness is assessed by the availability of ocean

			(FRK) performs dimension reduction through multi- resolution wavelet analysis so that it can dramatically reduce the computation cost of various kriging methods. However, the FRK cannot directly be used for incomplete data over spatially irregular regions such as SSTs, and the potential bias in the satellite data is not addressed.	pixels. The assessment results show that the spatially.
Addink, E. A.	A comparison of conventional and geostatistical methods to replace clouded pixels in NOAA-AVHRR images	*Int. J. Remote Sens.* vol. 20 no. 5 pp. 961–977 1999.	The potential of using National Oceanic and Atmospheric Administration (NOAA) Advanced Very High Resolution Radiometer (AVHRR) images for large areas is often limited by cloud cover. It could be increased when small clouds are replaced by estimated reflection and emission values. Images of subsequent days serve as co-variable, enabling the use of spatial and temporal information. Stratification of the image did not result in better cloud replacement. Once kriging options have been implemented in existing image processing packages, co-kriging will be an easy-to-use solution to missing values, provided that images of subsequent days of low cloud coverage	In this study seven replacement methods are compared, ranging from simple replacement to stratified co-kriging.For validation, cloud-free pixels were replaced with four patterns of artificially clouded pixels. Co-kriging as a combination of both temporal and spatial information resulted in the best estimates, reducing the mean squared errors by 20-70%.

			are available.	
Rossi, R. E., Dungan, J. L., Beck, L. R.	Kriging in the shadows: Geostatistical interpolation for remote sensing	*Remote Sens. Environ.* vol. 49 no. 1 pp. 32–40 1994.	It is often useful to estimate obscured or missing remotely sensed data. Traditional interpolation methods, such as nearest-neighbour or bilinear resampling, do not take full advantage of the spatial information in the image. An alternative method, a geostatistical technique known as indicator kriging, is described and demonstrated using a Landsat Thematic Mapper image in southern Chiapas, Mexico. The image was first classified into pasture and non-pasture land cover. For each pixel that was obscured by cloud or cloud shadow, the probability that it was pasture was assigned by the algorithm.	An exponential omnidirectional variogram model was used to characterize the spatial continuity of the image for use in the kriging algorithm. Assuming a cutoff probability level of 50%, the error was shown to be 17% with no obvious spatial bias but with some tendency to categorize non-pasture as pasture (overestimation). While this is a promising result, the method's practical application in other missing data problems for remotely sensed images will depend on the amount and spatial pattern of the un-obscured pixels and missing pixels and the success of the spatial continuity model used.
Chen, J., Zhu, X., Vogelmann, J. E.,	A simple and effective method for filling gaps in landsat ETM+ SLC-off images	*Remote Sens. Environ.* vol. 115 no. 4	The scan-line corrector (SLC) of the Landsat 7 Enhanced Thematic Mapper Plus (ETM+) sensor failed in 2003, resulting in about 22% of the pixels per scene not being scanned. The SLC failure has seriously limited the scientific applications of ETM+ data.	Results indicate that NSPI can restore the value of un-scanned pixels very accurately, and that it works especially well in heterogeneous regions. In addition, it can work well even if there is a relatively long time

Gao, F., Jin, S.		pp. 1053–1064 2011.	While there have been a number of methods developed to fill in the data gaps, each method has shortcomings, especially for heterogeneous landscapes. Based on the assumption that the same-class neighboring pixels around the un-scanned pixels have similar spectral characteristics, and that these neighboring and un-scanned pixels exhibit similar patterns of spectral differences between dates, we developed a simple and effective method to interpolate the values of the pixels within the gaps. Simulated and actual SLC-off ETM+ images were used to assess the performance of the NSPI. In addition, the simple principle and high computational efficiency of NSPI will enable processing large volumes of SLC-off ETM+ data.	interval or significant spectral changes between the input and target image. The filled images appear reasonably spatially continuous without obvious striping patterns.Supervised classification using the maximum likelihood algorithm was done on both gap-filled simulated SLC-off data and the original "gap free" data set, and it was found that classification results, including accuracies, were very comparable. This indicates that gap-filled products generated by NSPI will have relevance to the user community for various land cover applications.
Zhu, X., Liu, D., Chen, J.	A new geostatistical approach for filling gaps in Landsat ETM+ SLC-off images	*Remote Sens. Environ.* vol. 124 pp. 49–60 2012.	Since the failure of scan-line corrector (SLC) of the Landsat 7 Enhanced Thermal Mapper Plus (ETM+) sensor, a number of methods have been developed to fill the un-scanned gaps in ETM+ images. Unfortunately, the quality of the images filled by most of these existing methods is still not	This study proposes a new gap-filling method called Geostatistical Neighborhood Similar Pixel Interpolator (GNSPI) by improving the NSPI method using geostatistical theory. The simulation study shows that: compared with

			satisfactory, particularly in heterogeneous regions. Recently, a Neighborhood Similar Pixel Interpolator (NSPI) was developed that can accurately fill gaps in SLC-off images even in heterogeneous regions. However, the NSPI method is a type of deterministic interpolation approach that sets its weight parameters empirically and cannot provide statistical uncertainty of prediction.	previous geostatistical methods, the image filled by GNSPI has fewer striping effects; compared with NSPI, GNSPI is less empirical in its weight parameters and can provide uncertainty of prediction. More importantly, it can generate more accurate results than NSPI, especially when there is a long time interval between the input auxiliary image and the target SLC-off image.
Beckers, J. M. , Rixen	EOF calculations and data filling from incomplete oceanographic datasets	*J. Atmos. Ocean. Technol.* vol. 20 no. 12 pp. 1839–1856 2003.	This new method allows for the detectionof the number of statistically significant EOFs by a cross-validation procedure for a complete or incompletedataset, as well as the noise level and interpolation error. Since the proposed filling and analysis method doesnot need a priori information about the error covariance structure, the method is self-consistent and parameterfree.	The paper presents a new self-consistent method to infer missing data from oceanographic data series and toextract the relevant empirical orthogonal functions.
Poggio, L., Gimona, A.,	Spatio-temporal MODIS EVI gap filling under cloud cover: An example	*ISPRS J. Photogramm. Remote Sens.*	Time series of satellite data have an important role in the monitoring of regional and global ecosystem properties. Satellite images often	The aim of this study was to propose and test a spatio-temporal interpolation method to reconstruct pixel values in

Brown, I.	in Scotland	vol. 72 pp. 56–72 Aug. 2012. F. Gerber. (2017). *Gapfill: Fill Missing Values in Satellite Data R Package Version 0.9.5-3*. [Online]. Available: https://CRAN.R-project. org/package=gapfill	present missing data due to atmospheric aerosol, clouds or other atmospheric conditions. Most methods proposed to minimize the effects of degradation and to restore signal values do not take into account the spatial and temporal correlation of the values in the pixels. The method presented and tested is an example of a hybrid Generalised Additive Model (GAM)-geostatistical space-time model, including the fitting of a smoother spatio-temporal trend and a spatial component to account for local details supported by information in covariates. The method is not limited by the type of noise or degradation of pixels values, latitude, vegetation dynamics and land uses. The application of cloud masks on the target image provided the data for a quantitative validation through the comparison between the modelled EVI values and those from the MODIS product. The spatio-temporal method always performed better and the use of kriged residuals was helpful for situations with high percentages of missing data. The spatial pattern and the local features	MODIS data time series that are missing due to cloud cover or other image noise.The method was able to restore data providing very good to adequate responses in series of simulations of missing data. The comparison of distributions showed good agreement and predictive capabilities.The method has proved to be flexible and able to provide reconstructed images reproducing spatial patterns and local features of the measured product, even with substantial amounts of missing pixels.

			were well preserved for cloud coverage ⩽20%. For higher percentages of missing data, the results were smoother with less local detail retained.	
Weiss, D. J., Atkinson, P. M., Bhatt, S., Mappin, B., Hay, S. I., Gething, P. W.	An effective approach for gap-filling continental scale remotely sensed time-series	*ISPRS J. Photogramm. Remote Sens.* vol. 98 pp. 106–118 Dec. 2014.	The archives of imagery and modeled data products derived from remote sensing programs with high temporal resolution provide powerful resources for characterizing inter- and intra-annualenvironmental dynamics. The impressive depth of available time-series from such missions (e.g., MODIS and AVHRR) affords new opportunities for improving data usability by leveraging spatialand temporal information inherent to longitudinal geospatial datasets. Validation was done by introducing and filling artificial gaps, and thencomparing the original data with model predictions. The approach achieved R values above 0.87 even for pixels within 500 km wide introduced gaps. Furthermore, the structure of the approach allows estimation of the error associated with each gap-filled pixel based on the distance to the non-gap pixels used to model its fill value.	In this research they develop an approach for filling gaps in imagery time-series that result primarily from cloud cover, which isparticularly problematic in forested equatorial regions. The approach consists of two, complementary gap-filling algorithms and a variety of run-time options that allow users to balance competingdemands of model accuracy and processing time. They applied the gap-filling methodology to MODIS Enhanced Vegetation Index (EVI) and daytime and nighttime Land Surface Temperature (LST) datasets for the African continent for 2000–2012, with a 1 km spatial resolution, and an 8-day temporal resolution.

Lguensat, R., Tandeo, P.., Fablet, R., Garello, R.	Spatio-temporal interpolation of sea surface temperature using high resolution remote sensing data	in *Proc. Oceans-St. John's* 2014 pp. 1–4.	This work resolves the system iteratively using an ensemble Kalman filter and smoother. The methodology to remote sensing data of Sea Surface Temperature (SST) is presented. It uses high resolution SST maps provided by an infrared sensor, sensible to the presence of cloud. Comparing the results with the reference SST reanalysis.	In this work a statistical model to generate relevant reanalysis of geophysical parameters is presented and in particular, a stochastic equation to control the temporal and spatial variability of the signal are taken into account the possible error of the observations. Itdemonstrates the capability to interpolate missing data and keep into account the spatial and temporal consistency of the SST signal.
de Oliveira, J. C., Epiphanio, J. C. N., Rennó, C. D.	Window regression: A spatial-temporal analysis to estimate pixels classified as low-quality in MODIS NDVI time series	*Remote Sens.* vol. 6 no. 4 pp. 3123–3142 2014.	MODerate resolution Imaging Spectroradiometer (MODIS) data are largely used in multitemporal analysis of various Earth-related phenomena, such as vegetation phenology, land use/land cover change, deforestation monitoring, and time series analysis. The MODIS products used to undertake multitemporal analysis are composite mosaics of the best pixels over a certain period of time. However, it is common to find bad pixels in the composition that affect the time series analysis. This methodology, called Window Regression (WR), estimates	It presents a filtering methodology that considers the pixel position (location in space) and time (position in the temporal data series) to define a new value for the bad pixel.The method presented and other techniques (4253H twice, Mean Value Iteration (MVI) and Savitzky–Golay) were evaluated using the Mean Absolute Percentage Error (MAPE) and Akaike Information Criteria (AIC). The tests revealed the consistently superior

			the value of the point of interest, based on the regression analysis of the data selected by a spatial-temporal window. The spatial window is represented by eight pixels neighboring the pixel under evaluation, and the temporal window selects a set of dates close to the date of interest (either earlier or later). Intensities of noises were simulated over time and space, using the MOD13Q1 product.	performance of the Window Regression approach to estimate new Normalized Difference Vegetation Index (NDVI) values irrespective of the intensity of the noise simulated.
de Oliveira, J. C., Epiphanio, J. C. N.,	Noise reduction in MODIS NDVI time series data based on spatial-temporal analysis	In*Proc. IEEE Int. Geosci. Remote Sens. Symp. (IGARSS)* Jul. 2012 pp. 2372–2375.	Normalized Difference Vegetation Index is a vegetation index widely applied in research. However, noise induced by cloud contamination and atmospheric variability affect the data quality. The first task was to identify the pixels with the lowest guarantee of quality. The next step was to recalculate the NDVI values based on spatial and temporal correlations. The MOD13Q1 product was analyzed over a period of one year.	We propose the reconstruction of time series of MODIS NDVI data based on a quality assessment of the science data sets and on a spatial-temporal analysis of the low quality pixels. The results indicate that the spatial-temporal information, combined with pixel quality assessment, is a promising method for reconstructing high-quality MODIS NDVI time series.
Golyandina,N., Osipov, E.	The 'Caterpillar'-SSA method for analysis of time series with missing	*J. Stat. Planning Inference*	The paper concerns the problem of applying Singular Spectrum Analysis to timeseries with missing data. A method of filling in the missing data is	The proposed algorithms result in extraction of additive componentsof time series such as trends and periodic components,

	values	vol. 137 no. 8 pp. 2642–2653 2007.	proposed and isapplied to time series of finite rank. Conditions of exact reconstruction of missingdata are constructed and versions of the algorithm applicable to real-life time seriesare presented.	with simultaneous filling inthe missing data.
Guo, L., Lei, L., Zeng, Z. C., Zou, P., Liu, D., Zhang, B.	Evaluation of spatio-temporal variogram models for mapping Xco2 using satellite observations: A case study in China	*IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens.* vol. 8 no. 1 pp. 376–385 Jan. 2015.	Greenhouse Gases Observing Satellite (GOSAT),which measures column-averaged carbon dioxide dry air molefractions (Xco2) from space, provides new data sources to improveour understanding of carbon cycle. The available GOSAT data have many gaps and are irregularly positioned, whichmake it difficult to directly interpret their scientific significancewithout further data analysis. Spatio-temporal geostatisticalpredictionapproach can be used to fill the gaps for global andregional Xco2 mapping. It is important to choose a suitable spatiotemporalvariogram model since modeling spatio-temporal correlationstructure using variogram model is a critical step in the geostatisticalprediction. Thethree models are compared and evaluated	In this study, three different flexible spatio temporal ariogram models, including the product-sum model,Cressie–Huang model, and Gneiting model, are used to modelthespatio-temporal correlation structure of Xco2 over Chinausing the Atmospheric CO2 Observations from Space retrievalsof the GOSAT (ACOS-GOSAT) Xco2 (v3.3) data products. All the three variogram models can precisely catch theempiricalcharacteristics of the spatio-temporal correlation structureof Xco2 over China, and the precision and effectiveness ofpredicting and mapping Xco2 using the three models are almostthe same.

			using the weightedmean square errors (WMSE) indicating the fitness between theempiricalvariogram surface and the theoretical variogrammodel,cross-validation for quantifying prediction accuracies, and theperformance of the three models when used to fill the spatialgaps.	
Zeng, Z.; Lei, L.; Hou, S.; Ru, F.; Guan, X.; Zhang, B.	A regional gap-filling method based on spatiotemporal variogram model of CO2 columns	*IEEE Trans. Geosci. Remote Sens.* vol. 52 no. 6 pp. 3594–3603 Jun. 2014. D. P. Roy J. S. Borak S.	A precise and high-resolution spatiotemporal distribution of atmospheric carbon dioxide (CO 2) is important in identifying and quantifying the CO 2 source and sinks on regional scales and emissions from discrete point sources. The accuracy of the gap-filling results is verified by cross-validation and comparison with ground-based measurements. A comparison on the prediction accuracy based on the method with that based on the commonly used spatial-only kriging to further demonstrate the improved prediction accuracy. The applied regional gap-filling method, which makes full use of the multitemporal ACOS-GOSAT data, can generate a regional regular spatial distribution map of (Xco2) at high	The work propose the use of a regional gap-filling method by modeling the spatiotemporal correlation structures of column-averaged CO 2 dry air mole fractions (Xco 2) on a regional scale, using data from the Atmospheric CO 2 Observations from Space retrievals of the Greenhouse Gases Observing Satellite (ACOS-GOSAT) measurements over mainland China. The results of the spatiotemporal gap-filling method are applied to mainland China, the correlation coefficient (r 2) between the predicted values and true ones is greater than 0.85, the mean absolute prediction error is less than 1.5

			spatial and temporal resolutions.	ppm in cross-validation, and the seasonal cycle of the gap-filled data is generally in agreement with ground-based measurements.
Qiang Zhang, Qiangqiang Yuan, Chao Zeng, Xinghua Li, Yancong W	Missing Data Reconstruction in Remote Sensing Image With a Unified Spatial–Temporal–Spectral Deep Convolutional Neural Network	*IEEE Trans. Geosci. Remote Sens.* vol. 56 no. 8 pp. 4274-4288 Aug. 2018.	The unified spatial-temporal-spectral framework based on a deep convolutional neural network (CNN) employs a unified deep CNN combined with spatial-temporal-spectral supplementary information. In addition, to address the fact that most methods can only deal with a single missing information reconstruction task, the proposed approach can solve three typical missing information reconstruction tasks: (1) dead lines in Aqua Moderate Resolution Imaging Spectroradiometer band 6; (2) the Landsat Enhanced Thematic Mapper Plus scan line corrector-off problem; and (3) thick cloud removal. It should be noted that the proposed model can use multisource data (spatial, spectral, and temporal) as the input of the unified framework. The results of both simulated and real-data experiments demonstrate that the proposed model	Differing from most of the inpainting methods, the proposed STS-CNN model can recover different types of missing information. To promote the reconstruction precision, some specific structures are employed in the network to enhance the performance. Although the proposed method performs well for reconstructing the dead lines in Aqua MODIS band 6, the ETM+ SLC-off problem, and thick cloud removal, it still has some unavoidable limitations. When removing thick cloud through the use of temporal information, it results in some spectral distortion and blurring. Another possible strategy is adding an *a priori* constraint (such as NSPI, locality-adaptive discriminant analysis, embedding

			exhibits high effectiveness in the three missing information reconstruction tasks listed above.	structured contour and location, and context transfer) to reduce the spectral distortion and improve the texture details.
Michael Kwok-Po Ng, Qiangqiang Yuan, Li Yan, Jing Sun	An Adaptive Weighted Tensor Completion Method for the Recovery of Remote Sensing Images With Missing Data	*IEEE Trans. Geosci. Remote Sens.* vol. 55 no. 6 pp. 3367-3381 June 2017.	An adaptive weighted tensor completion (AWTC) method for the recovery of remote sensing images with missing data. Collectively make use of the spatial, spectral, and temporal information to build a new weighted tensor low-rank regularization model for recovering the missing data. Experimental results based on both simulated and real data sets are presented to verify that the proposed method can recover missing data, and its performance is found to be better than the other tested methods.	The missing information reconstruction problem is defined as a weighted tensor rank minimization problem. Considering the low-rank strength in different unfoldings of the tensor data, an adaptive way to determine the weight, and form the AWTC model is proposed. Finally, the very popular ADMM method is used to optimize the model. Although the proposed AWTC model performs well, it still has some limitations. In the multitemporal reconstruction experiments, the time dimension is stacked together with the spectral dimension, which results in the complementary information from the time dimension not being fully explored. Another possible approach would be to define a fourth-order tensor with the spatial, spectral, and temporal information, and then define a high-order tensor low-rank

				model.

Peter Henderson, Riashat Islam, Philip Bachman, Joelle Pineau, DoinaPrecup, David Meger	Deep Reinforcement Learning that Matters	Technical report, McGill University and Microsoft Maluuba, 2017.	Significant progress has been made in solving challenging problems across various domains using deep reinforcement learning (RL). Reproducing existing work and accurately judging the improvements offered by novel methods is vital to sustaining this progress. Unfortunately, reproducing results for state-of-the-art deep RL methods is seldom straightforward. In particular, non-determinism in standard benchmark environments, combined with variance intrinsic to the methods, can make reported results tough to interpret. Without significance metrics and tighter standardization of experimental reporting, it is difficult to determine whether improvements over the prior state-of-the-art are meaningful.	In this paper, they investigate challenges posed by reproducibility, proper experimental techniques, and reporting procedures. Authors illustrated the variability in reported metrics and results when comparing against common baselines and suggest guidelines to make future results in deep RL more reproducible. They also aim to spur discussion about how to ensure continued progress in the field by minimizing wasted effort stemming from results that are non-reproducible and easily misinterpreted.
Alexandra L'Heureux, Katarina Grolinger, Hany F. Elyamany&	Machine Learning With Big Data: Challenges and Approaches	IEEE Access, VOLUME 5, 2017, pp. 7776-7797	The Big Data revolution promises to transform how we live, work, and think by enabling process optimization, empowering insight discovery and improving decision making. The realization of this grand	This work highlights the cause & effect relationship by organizing challenges according to Big Data Vs or dimensions that instigated the issue: volume, velocity,

Miriam A. M. Capretz			potential relies on the ability to extract value from such massive data through data analytics; machine learning is at its core because of its ability to learn from data and provide data driven insights, decisions, and predictions. However, traditional machine learning approaches were developed in a different era, and thus are based upon multiple assumptions, such as the data set fitting entirely into memory, what unfortunately no longer holds true in this new context. These broken assumptions, together with the Big Data characteristics, are creating obstacles for the traditional techniques. Consequently, this paper compiles, summarizes, and organizes machine learning challenges with Big Data.	variety, or veracity. Moreover, emerging machine learning approaches and techniques are discussed in terms of how they are capable of handling the various challenges with the ultimate objective of helping practitioner's select appropriate solutions for their use cases. Finally, a matrix relating the challenges and approaches is presented. Through this process, this paper provides a perspective on the domain, identifies research gaps and opportunities, and provides a strong foundation and encouragement for further research in the field of machine learning with Big Data.
Leon Bottou, Frank E. Curtisy, Jorge Nocedalz	**Optimization Methods for Large-Scale Machine Learning**	**SIAM Rev., 2018**	**This paper provides a review and commentary on the past, present, and future of numerical optimization algorithms in the context of machine learning applications. Through case studies on text classification and the training of deep neural networks. A major theme of our study is that**	**Authors, in this work had presented how optimization problems arise in machine learning and what makes them challenging. They presented a comprehensive theory of a versatile SG algorithm, discuss its practical behavior, and highlight opportunities for**

			large-scale machine learning represents a distinctive setting in which the stochastic gradient (SG) method has traditionally played a central role while conventional gradient-based nonlinear optimization techniques typically falter. This leads to a discussion about the next generation of optimization methods for large-scale machine learning, including an investigation of two main streams of research on techniques that diminish noise in the stochastic directions and methods that make use of second-order derivative approximations.	**designing algorithms with improved performance.**
Anders Arpteg, BjörnBrinne, Jan Bosch, Luka Crnkovic-Friis	**Software Engineering Challenges of Deep Learning**	**44th Euromicro Conference on Software Engineering and Advanced Applications in September 2018**	**The findings in this paper are based on seven example ML projects that have been carried out in close collaboration with companies of different sizes and types. The companies range from start-up size to large multinational companies with thousands of employees and many millions of active users. The examples are focused on ML projects of**	**This paper identifies and outlines the main software engineering challenges associated with building systems with deep learning components. Seven projects are described to exemplify the potential for making use of machine learning and specifically deep learning technology. Though the main focus of the paper is not to provide solutions, but rather**

			different types where some systems have been in production for more than 10 years, starting from 2005 and onward, and other systems are still in the prototype stage. Experience is collected from people directly employed in associated organizations and working with given case studies, taking a participant observer approach and making use of well-established case study methods.	**to outline problem areas and help guide future research. In addition, the outlined challenges also provide guidance on potential problem areas for companies interested in building high-quality deep learning systems.**
James Gerard Wolff	**The SP Theory of Intelligence: Distinctive Features and Advantages**	**IEEE Access, VOLUME 4, 2016**	**Authors presented a simple concepts in AI-related areas, which has potential to simplify and integrate of structures and processes in computing systems. Unlike most other AI-related theories, the SP theory is itself a theory of computing, which can be the basis for new architectures for computers. Fundamental in the theory is information compression via the matching and unification of patterns and, more specifically, via a concept of multiple alignment. It provides an interpretation of aspects of**	**This paper aims to highlight distinctive features of the SP theory of intelligence, realized in the SP computer model, and its apparent advantages compared with some AI-related alternatives.**

			mathematics and an interpretation of phenomena in human perception and cognition.	
Ramakrishna,M., Malladi, V., **AdibaNizami,** **Manju,S., Mahakali,** **Gopala Krishna, Barla**	**Cloud Masking Technique for High-Resolution Satellite Data:** **An Artificial Neural Network Classifier Using Spectral & Textural Context**	**Journal of the Indian Society of Remote Sensing April 2019, Volume 47, Issue 4, pp 661–670**	**A generic and efficient technique is attempted using the Cartosat-2 series (C2S) satellite which is having high-resolution multispectral sensor in the visible and near-infrared bands. The methodology is based on textural features from the available spectral context, and using a feed-forward neural network for the classificationis proposed. The method was shown to have an overall accuracy of 97.98% for a large manually pre-classified validation dataset with more than 2 million data points. Experimental results and cloud masks generated for various scenes show that the method may be viable as a reasonable cloud masking algorithm for C2S data.**	**An artificial neural network was developed and studied. It also uses a fully connectedfeed forward neural network with two hidden layers with 8 and 4 nodes, respectively. For training, the iRPROP algorithm is used. Limitation of this method is a large pre-classified validation dataset is required**
Guilin, Liu, **Fitsum, A., Reda,** **Kevin J. Shih,** **Ting-Chun, Wang,**	**Image Inpainting for Irregular Holes UsingPartial Convolutions**	**Computer Vision - {ECCV} 2018 - 15th European Conference, Munich, Germany, September 8-14, 2018, Proceedings,**	**Existing deep learning based image inpainting methods often leads to artefacts such as colour discrepancy and blurriness. Post-processing is usually used to reduce such artefacts, but is expensive and may fail. The use of partial convolutions, where the**	**This model can robustly handle holes of any shape, size location, or distance from the image borders.** **One limitation of our method is that it fails for some**

Andrew Tao, Bryan Catanzaro		**Part XI pp 89-105**	**convolution is masked and renormalized to be conditioned on only valid pixels is proposed. Further including a mechanism to automatically generate an updated mask for the next layer as part of the forward pass. This model out-performs other methods for irregular masks.**	**sparsely structured images such as the bars on the door in and, like most methods, struggles on the largest of holes.**
Ulyanov, DVedaldi, A Lempitsky, V.	**Deep Image Prior**	**Computer Science, April 2018.**	**Generally, for image generation and restoration, deep convolutional networks have excellent performance, imputed to their ability to learn realistic image priors from a large number of example images.** **This paper shows that, on the contrary, the structure of a generator network is sufficient to capture a great deal of low-level image statistics prior to any learning. Furthermore, the prior can be used to invert deep neural representations to diagnose them, and to restore images based on flash-no flash input pairs.** **This approach also highlights the inductive bias captured by standard generator network**	**Fitting a randomly-initialized ConvNet to corrupted images works as a "Swiss knife" for restoration problems. While practically slow (taking several minutes of GPU computation** **per image), this approach does not require modelling of the degradation process or pre-training. Our results go against the common narrative that explain** **the success of deep learning in image restoration to the ability** **to learn rather than hand-craft priors; instead, random networks are better hand-**

			architectures.	**crafted priors, and learning builds on this basis. This also validates the importance of developing new deep learning architectures.**
JuergenSchmidhuber	**Deep Learning in Neural Networks: An Overview.**	**Neural Networks, Jan 2015, Vol 61, pp 85-117**	**In recent years, deep artificial neural networks (including recurrent ones) have won numerous contests in pattern recognition and machine learning. This historical survey compactly summarises relevant work, much of it from the previous millennium. Shallow and deep learners are distinguished by the depth of their credit assignment paths, which are chains of possibly learnable, causal links between actions and effects. Deep supervised learning (also recapitulating the history of back propagation), unsupervised learning, reinforcement learning & evolutionary computation, and indirect search for short programs encoding deep and large networks.**	**Starting from recent deep learningresults, This book tries to trace back the origins of relevant ideas through the past half century and beyond, sometimes using "local search" to follow citations of citations backwards in time. Since not all deep learning publications properly acknowledge earlier relevant work, additional global search strategies were employed, aided by consulting numerous neural network experts. As a result, the present preprint mostly consists of references.**

3.4 A Brief summary of Reviewed Literature

Time Series reconstruction methodis applied for generic change detection approach by detecting and characterizing Breaks For Additive Seasonal and Trend(BFAST).[**Verbesselt, J., Hyndman, R., Newnham, G. ,&Culvenor,D., 2010]**. BFAST integrates the decomposition of time series into trend, seasonal, and remainder components with methods for detecting change within time series. BFAST is able to detect and characterize spatial and temporal changes in a forested landscape. BFAST also works for Phenological change detection while accounting for abrupt and gradual trends in satellite image time series. [**Verbesselt, J.,Hyndman, R.,Zeileis, A., Culvenor, D., 2010]**. A novel climatology fitting approach called CACAO (Consistent Adjustment of the Climatology to Actual Observations) is proposed to reduce noise and fill gaps in time series by scaling and shifting the seasonal climatological patterns to the actual observations. Results of simulation experiments as well as confrontation with actual AVHRR time series indicate that the proposed CACAO method is more robust to noise and missing data than AG and SG methods for phenology extraction **[Verger, A.; Baret, F.; Weiss, M.; Kandasamy, S.; Vermote, E., (2013)]**. Detecting Breakpoints and Estimating Segments in Trend (DBEST) uses a novel segmentation algorithm which simplifies the trend into linear segments using one of three user defined parameters: a generalization-threshold parameter δ, the m largest changes, or a threshold β for the magnitude of changes of interest for detection. The outputs of DBEST are the simplified trend, the change type (abrupt or non-abrupt), and estimates for the characteristics (time and magnitude) of the change **[Jamali, S.; Jönsson, P.; Eklundh, L.; Ardö, J.; Seaquist, J., (2015)]. Colditz, R. R.,Conrad, C.,Wehrmann, T., Schmidt, M.,Dech, S. in 2008,** proposed TiSeG: A flexible software tool for time-series generation of MODIS data utilizing the quality assessment science data set.

Savitzky-Golay Filter techniqueis applied by authoralong with iteratively re-weighted local regression filter (LOESS) in Noise reduction and gap filling of fAPAR (the fraction of absorbed photosynthetic active radiation) time **series [Moreno, A.; García-Haro, F. J.; Martínez, B.; Gilabert, M.A.,(2014)]**.TIMESAT—A program for analyzing time-series of satellite sensor data uses an adaptive Savitzky-Golay filtering method and newly developed methods based on upper envelope weighted fits to asymmetric Gaussian and double logistic model functions **[Jönsson, P., Eklundh, L., (2004)]**. **Chen, J.; Jonsson, P.; Tamura, M.; Gu, Z.H.;**

Matsushita, B.; Eklundh, L. in 2004, have developed a simple but robust method based on the Savitzky–Golay filter to smooth out noise in NDVI time-series, specifically that caused primarily by cloud contamination and atmospheric variability.

Fourier analysisis applied inGlobal data for ecology and epidemiology: A novel algorithm for temporal Fourier processing MODIS data **[Scharleman, J. P. W., n*et al.,(2008)*]**. The novel spline-based algorithm is tested on artificial data generated using randomly selected values of both amplitudes and phases, and provides an accurate estimate of the input variables under all conditions.

It is often useful to estimate obscured or missing remotely sensed data. Traditional interpolation methods, such as nearest-neighbour or bilinear resampling, do not take full advantage of the spatial information in the image. An alternative method, a geostatistical technique known as indicator kriging, is described and demonstrated using a Landsat Thematic Mapper image. Kriging and co-kriging methods are used for improving the spatial completeness and accuracy of satellite images **[Addink, E.A. in 1999 and Zhu, Y., Kang, E. L., Bo, Y., Tang, Q., Cheng, J., He, Y. in 2015]**. A new gap-filling method called Geostatistical Neighborhood Similar Pixel Interpolator (GNSPI) was used for filling gaps in Landsat ETM+ SLC-off images **[Zhu, X., Liu, D., Chen, J., (2012)]**. Many authors have applied Spatio-temporal interpolation and analysis for correcting gaps in satellite data. **De Oliveira, J. C., Epiphanio, J. C. N., Rennó, C. D. in 2014** used Window regression technique is used which is a spatial-temporal analysis to estimate pixels classified as low-quality in MODIS NDVI time series. MODerate resolution Imaging Spectroradiometer (MODIS) data are largely used in multitemporal analysis of various Earth-related phenomena, such as vegetation phenology, land use/land cover change, deforestation monitoring, and time series analysis. This method uses a filtering methodology that considers the pixel position (location in space) and time (position in the temporal data series) to define a new value for the bad pixel. The method presented and other techniques, Mean Value Iteration (MVI) and Savitzky–Golay were evaluated using the Mean Absolute Percentage Error (MAPE) and Akaike Information Criteria (AIC). The tests revealed the consistently superior performance of the Window Regression approach to estimate new Normalized Difference Vegetation Index (NDVI) values irrespective of the intensity of the noise simulated. **Golyandina,N., Osipov, E. in 2007** have expressed the problem of applying Singular Spectrum Analysis to time series with

missing data. The proposed algorithms result in extraction of additive components of time series such as trends and periodic components.

Neural Networks and Deep Learning techniques and models:

Qiang Zhang, Qiangqiang Yuan, Chao Zeng ,Xinghua Li, Yancong W in 2018 have applied a Unified Spatial–Temporal–Spectral Deep Convolutional Neural Network to fill the gaps in RS data. Significant progress has been made in solving challenging problems across various domains using deep reinforcement learning (RL) **[Peter Henderson, Riashat Islam, Philip Bachman, Joelle Pineau, DoinaPrecup, David Meger in 2017]**.The Big Data revolution promises to transform how we live, work, and think by enabling process optimization, empowering insight discovery and improving decision making. The realization of this grand potential relies on the ability to extract value from such massive data through data analytics; machine learning is at its core because of its ability to learn from data and provide data driven insights, decisions, and predictions. However, traditional machine learning approaches were developed in a different era, and thus are based upon multiple assumptions such as the data set fitting entirely into memory, what unfortunately no longer holds true in this new context. **Alexandra L'Heureux, Katarina Grolinger, Hany F. Elyamany& Miriam A. M. Capretz in 2017**provide a perspective on the domain, identifies research gaps and opportunities, and provides a strong foundation and encouragement for further research in the field of machine learning with Big Data.

Bottou, Leon; Frank E. Curtisy; Nocedalz, Jorge in 2018provides a review and commentary on the past, present, and future of numerical optimization algorithms in the context of machine learning applications. A comprehensive theory of a versatile stochastic gradient (SG) algorithm is presented, to discuss its practical behavior, and highlight opportunities for designing algorithms with improved performance. **Arpteg, Anders; BjörnBrinne; Bosch, Jan; Crnkovic-**

Friis, Luka in 2018, identifies and outlines the main software engineering challenges associated with building systems with deep learning components. **Gerard Wolff, James (2016)**talks about The SP Theory of Intelligence: Distinctive Features and Advantages.Unlike most other AI-related theories, the SP theory is itself a theory of computing, which can be the basis for new architectures for computers. Fundamental in the theory is information compression via the matching and unification of patterns and, more specifically, via a concept of multiple alignment. It provides an interpretation of aspects of mathematics and an interpretation of phenomena in human perception and cognition.

4. Motivation/Justification and Relevance

Use of remote sensing data is widely done to study range of earth surface processes. The data obtained from satellites have the advantage of extensive spatial and temporal coverage. However, many time data sets derived from optical satellite sensors partially show clouds instead of the Earth's surface. Further, several times the data may be of low quality due to technical glitches and get a miss for some unavoidable human errors. Several attempts were made to bridge the missing data. Number of satellite-derived time series reconstruction methods have been developed, for instance, the Savitzky–Golay filter, the Fourier analysis, the wavelet transform, and function fitting.

- **Savitzky–Golayfilter:**

A Savitzky–Golay filter is a digital filter that can be applied to a set of digital data points for the purpose of smoothing the data, that is, to increase the signal-to-noise ratio without greatly distorting the signal. This is achieved, in a process known as convolution, by fitting successive sub-sets of adjacent data points with a low-degree polynomial by the method of linear least squares.

- **Fourier analysis:**

In mathematics, Fourier analysis is the study of the way general functions may be represented or approximated by sums of simpler trigonometric functions. It has many scientific applications – in physics, partial differential equations, number theory, combinatorics, signal processing, digital image processing, probability theory, statistics, forensics, option pricing, cryptography, numerical analysis, acoustics, oceanography, sonar, optics, diffraction, geometry, protein structure analysis, and other areas in signal processing. When processing signals, such as audio, radio waves, light waves, seismic waves, and even images, Fourier analysis can isolate narrowband components of a compound waveform, concentrating them for easier detection or removal. Some examples where Fourier analysis is used,include:Image processing to remove periodic or anisotropic artifacts such as jaggies from interlaced video, strip artifacts from strip aerial photography, or wave patterns from radio frequency interference in a digital camera;Cross correlation of similar images for co-alignment.

- **Wavelet transform:**

In mathematics, a wavelet series is a representation of a square-integrable (real- or complex-valued) function by a certain orthonormal series generated by a wavelet. This article provides a formal, mathematical definition of an orthonormal wavelet and of the integral wavelet transform.

The fundamental idea of wavelet transforms is that the transformation should allow only changes in time extension, but not shape. This is affected by choosing suitable basis functions that allow for this. The transformed signal provides information about the time and the frequency.

Therefore, wavelet-transformation contains information similar to the short-time-Fourier-transformation, but with additional special properties of the wavelets, which show up at the resolution in time at higher analysis frequencies of the basis function.

- **Curve Fitting:**

Curve fitting is the process of constructing a curve, or mathematical function, that has the best fit to a series of data points, possibly subject to constraints. Curve fitting can involve either interpolation, where an exact fit to the data is required, or smoothing, in which a "smooth" function is constructed that approximately fits the data. Fitted curves can be used as an aid for data visualization, to infer values of a function where no data are available, and to summarize the relationships among two or more variables.

4.1Gaps in Remote Sensing data

Remote Sensing data acquired from satellites often shows gaps and the data is not continuous. The major reasons accounting for these gaps can be classified under the following broad categories:

- Unavailability of constellation of satellites resulting in limited Remote Sensing data.
- No Data Acquisition orbit over that place at that particular time, fixed revisit period of satellites.
- Not many satellites using sensors with thermal, multispectral or hyperspectral bands.
- Most of the sensors are using Optical and NIR range of electromagnetic spectrum. Recently started with Indian satellites using active remote sensing in Microwave range.
- Tilting of camera sometimes may result in missing of data.
- Missing data due to cloud coverage.
- Missing data due to atmospheric aerosol or other atmospheric conditions.
- Data loss due to mis-registration of bands.
- Improper data due to vertical striping, line losses, pixel losses etc.
- Non-uniform response of Charged Coupled Devices.
- Geometric and Radiometric errors in data.

These results in missing observations, i.e., gaps, due to the orbit and sensing geometry, data acquisition strategy, and cloud contamination.This happens more in the cases of passive satellites which work in visible range, SWIR or VNIR range of Electromagnetic spectrum. Many time data sets derived from optical satellite sensors partially show clouds instead of the Earth's surface. Further, several times the data may be of low quality due to technical glitches and get a miss for some unavoidable human errors. Several attempts were made to bridge the missing data. Numbers of satellite-derived time series reconstruction methods, cloud computation methods

have been developed, for instance, the Savitzky–Golay filter, the Fourier analysis, the Wavelet Transform, and Function Fitting.

4.2 Comparison of the methods

It is observed that the existing functions may not perform well with less high-quality observations and are limited by insufficient temporal information. Before doing the comparison few limitations may first be categorized as follows:

Predictions partially fail when missing values are within large gaps.

Lack of quantification of prediction uncertainties

Non-availability of well-documented open-source software.

Non-scalability to large data sets.

Methods may work well in a few domains like Spatial or Temporal or Spatio-Temporal but may not work efficiently in all these domains.

Also, lot of manual intervention and expertise is required to apply these methods. They may not work well with all the resolutions and terrains.The methods which are compared in three domains; namely Spatial, Temporal and Spatio-temporal with various data sets and on different platforms are shown in the table 1.

	Method	Details	Language
Temporal	BFAST	Breaks For Additive Season and Trend	R*
	CACAO	Consistent Adjustment of Climatology to Actual Observations	-
	DBEST	Detecting Breakpoints and Estimating Segments in Trend	R*
	HANTS	Harmonic Analysis of Time-Series	Matlab, Fortan
	LOESS	Locally wEighted Scatterplot Smoothing	IDL
	NEURAL NETWORKS	Neural Networks combined with Savitzky-Golay functions	-
	SPLINES	Spline models with elevation as additional variable	GRASS GIS*
	SPLINES and FOURIER	Linear and Spline models combined with Fourier Analysis	quickBasic
	TIMESAT	Savitzky-Golay, asymmetric Gaussian, double logistics functions	Matlab, Fortran
	TiScG	Time-Series Generator for MODIS data	IDL
Spatial	CO-KRIGING	Spatial Variogram models	-
		GeostatisticalNeighbourhood Similar pixel Interpolator	-
Spatio - temporal	EOF	Empirical Orthogonal Functions	
	GAM and KRIGING	Generalized Additive Model and Kriging	GRASS GIS, R*
	GAPFILL	Quantile Regressions fitted to spatio-temporal subsets	R, C++ *
	GAPFILL-MAP	Prediction method used in the Malaria Atlas Project	Python, C *
	KALMAN-FILTERING	Monte Carlo version of Kalman-filtering	-
	LINEAR REGRESSION	Linear Regressions fitted to spatio-temporal subsets	-
	SSA	Singular Spectrum Analysis	R*
	SPACE-TIME KRIGING	Spatio-temporal variogram models	-

Thus, we may like to explore another mechanism which probably gives better results in all the three domains.

4.3 Deep Learning & its applicability to Remote Sensing Area

The data obtain from Remote Sensing (RS) is used in many fields and domains and is indispensable nowadays as this data plays a vital role in the socio-economic growth of country and helps in effective decision making.

Artificial intelligence approaches are getting increasingly prevalent to solve multi-disciplinary problems as they are adaptive and impart autonomy. An artificial neural network (ANN) is built to model the human brain's own nervous system. It consists of objects called nodes, or neurons, arranged in various layers called input, output and hidden layers. There is typically only oneinput, one output and one or several hidden layers. A bias node is usually added to each layer except the output layer to enable better performance of the network. Each node is connected to all the nodes in the subsequent layer through weighted paths. The activity of a node is the result of an activation function which is fed with the sum of all the weighted inputs. Various activation functions are used like the sigmoid function or the *tanh* function. The ANN may be fully connected or not, though fully connected ANNs are normally preferred. The complexity of a neural network can vary from a simple one with a single hidden layer to a large neural network with multiple hidden layers called a deep neural network (Schmidhuber 2015) .

The number of input and output neurons depends on the problem to be solved by the network. In a way, a neural network may be viewed as a nonlinear vector-valued function. Different types of neural networks like a feedforward ANN (Hornik 1989), convolutional neural network (Lecun et al. 1998) or recurrent neural network (Martens and Sutskever 2011) exist. **Deep Learning** is an emerging area of Machine Learning, typically based on learning data representations, as opposed to task-specific algorithms. Itis an aspect of artificial intelligence (AI) that is concerned with emulating the learning approach that human beings use to gain certain types of knowledge.

Since plenty of data is available nowadays from multiple varied sources and incoming data is huge, advanced technologies which are data driven compared to earlier task driven methods can be adopted and Deep Learning is one such area which may provide solution to our problem of bridging gaps in RS data. Deep learning has been successfully applied toinverse problemssuch asdenoising,super-resolution,in painting, andfilm colorization. These applications include learning methods such as "Shrinkage Fields for Effective Image Restoration" which trains on an image dataset, and*Deep Image Prior* , which trains on the image that needs restoration.

4.4 Methodology in Deep Learning

Algorithm in deep learning applies a nonlinear transformation on its input and uses what it learns to create a statistical model as output. Each level learns to transform its input data into a slightly more abstract and composite representation. Iterations continue until the output has reached an acceptable level of accuracy. The number of processing layers through which data must pass is

what inspired the label *deep*. These **features & processes** facilitate automatic learning at multiple levels of abstraction, allowing a system to learn complex functions mapping of the input to the output directly from data, without depending completely on human-crafted features.

Deep learning systems have a substantial*credit assignment path*(CAP) depth. The CAP is the chain of transformations from input to output. CAPs describe potentially causal connections between input and output. For a*feedforward neural network*, the depth of the CAPs is that of the network and is the number of hidden layers plus one (as the output layer is also parameterized). For*recurrent neural networks*, in which a signal may propagate through a layer more than once, the CAP depth is potentially unlimited.No universally agreed upon threshold of depth divides shallow learning from deep learning, but most researchers agree that deep learning involves CAP depth > 2. CAP of depth 2 has been shown to be a universal approximator in the sense that it can emulate any function. Beyond that more layers do not add to the function approximator ability of the network. Deep models (CAP > 2) are able to extract better features than shallow models and hence, extra layers help in learning features. Deep learning architectures are often constructed with a*greedy*layer-by-layer method. Deep learning helps to disentangle these abstractions and pick out which features improve performance.

Although early approaches published by Hinton and collaborators focus on greedy layer wise training and unsupervised methods like auto encoders, modern state-of-the-art deep learning is focused on training deep (many layered) neural network models using the back propagation algorithm. The most popular techniques are:

- Multilayer Perceptron Networks.
- Convolutional Neural Networks.
- Long Short-Term Memory Recurrent Neural Networks.

5. Objectives

- To study Deep Learning methods, algorithms and architecture.
- To examine these techniques on remote sensing data and propose changes in existing algorithms to improvise its applicability to a wider data set.
- To apply proposed algorithm and/or model for reconstructing remote sensing images by filling gaps.
- To examine the quality of the output received and analyze it for remote sensing data.
- To compare the effectiveness of the proposed algorithm with the output received using traditional methods.

6. Hypotheses

Hypothesis 1:

Deep Learning techniques will work more efficiently with less manual intervention.

Hypothesis 2:

It will take comparatively less time to generate the output – reconstruct the gap in the remote sensing images.

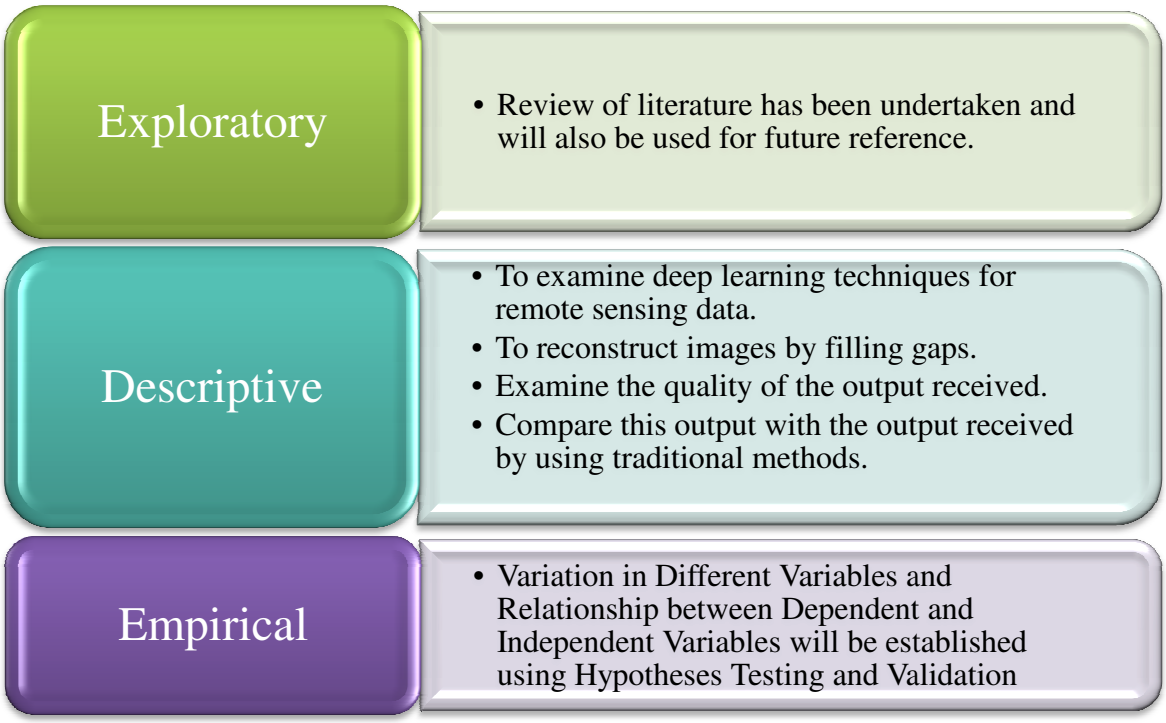
Hypothesis 3:

The output will be better as compared to traditional methods.

7. Plan of Work and Methodology

7.1 Research Design

The different objectives of the proposed study will be based on the following Research Designs:


Exploratory
• Review of literature has been undertaken and will also be used for future reference.
Descriptive
• To examine deep learning techniques for remote sensing data.
• To reconstruct images by filling gaps.
• Examine the quality of the output received.
• Compare this output with the output received by using traditional methods.
Empirical
• Variation in Different Variables and Relationship between Dependent and Independent Variables will be established using Hypotheses Testing and Validation

7.2 Data Collection

Remote Sensing data sets are widely available and are continuously obtained.

7.3 Universe and Sample of the study

The data will be of different regions, terrains, and time periods.

Data under study will contain different dimensions and features.

7.4 Tools and Techniques

In order to fulfill the objectives of the proposed Study, a few ***Tools***which are used so far are listed below:

Jupyter Notebook,

Python programming language, numPy library,

Google Colabs and GPU computations

U-Net architecture

8. Place of Work and Facilities Available

My work place – National Remote Sensing Centre, ISRO, Hyderabad.

9 Limitations

It is too early to enumerate the limitations of the proposed study.

10 References

- Verbesselt, J.; Hyndman, G.; Newnham, G.; Culvenor, D. (2010). Detecting trend and seasonal changes in satellite image time series. Remote Sens.Environ. 2010, 114, pp. 106–115.

- Verbesselt, J.; Hyndman, R.; Zeileis, A.; Culvenor, D. (2010).Phenological change detection while accounting for abrupt and gradual trends in satellite image time series. Remote Sens. Environ.2010,114, pp. 2970–2980.
- Verger, A.; Baret, F.; Weiss, M.; Kandasamy, S.; Vermote, E. (2013).The CACAO method for smoothing gap filling and characterizing seasonal anomalies in satellite time series. IEEE Trans. Geosci. Remote Sens.2013, 51,pp. 1963–1972.

- Jamali, S.; Jönsson, P.; Eklundh, L.; Ardö, J.; Seaquist, J. (2015). Detecting changes in vegetation trends using time series segmentation. Remote Sens. Environ.2015, 156,pp. 182–195.

- Chen, J.; Jonsson, P.; Tamura, M.; Gu, Z.H.; Matsushita, B.; Eklundh, L. (2004). A simple method for reconstructing a high-quality NDVI time-series data set based on the Savitzky–Golay filter. Remote Sens. Environ. 2004, 91, pp. 332–344.

- Olsson, L.; Eklundh, L. (1994). Fourier-series for analysis of temporal sequences of satellite sensor imagery. Int. J. Remote Sens. 1994, 15, pp. 3735–3741.

- Roerink, G.J.; Menenti, M.; Verhoef, W. (2000). Reconstructingcloudfree NDVI composites using Fourier analysis of time series. Int. J. Remote Sens. 2000, 21, pp. 1911–1917.

- Moody, A.; Johnson, D.M. (2001). Land-surface phenologies from AVHRR using the discrete Fourier transform. Remote Sens. Environ. 2001, 75, pp. 305–323.

- Yang, G.; Shen, H.; Zhang, L.; He, Z.; Li, X. (2015). A moving weighted harmonic analysis method for reconstructing high-quality SPOT VEGETATION NDVI time-series data. IEEE Trans. Geosci. Remote Sens. 2015, 53, pp. 6008–6021.

- Sakamoto, T.; Yokozawa, M.; Toritani, H.; Shibayama, M.; Ishitsuka, N.; Ohno, H.(2005). A cropphenology detection method using time-series MODIS data. Remote Sens. Environ. 2005, 96, pp. 366–374.

- Lu, X.; Liu, R.; Liu, J.; Liang, S. (2007). Removal of noise by wavelet method to generate high quality temporal data of terrestrial MODIS products. Photogramm. Eng. Remote Sens. 2007, 73, pp. 1129–1139.

- Qiu, B.; Feng, M.; Tang, Z. (2016)A simple smoother based on continuous wavelet transform: Comparative evaluation based on the fidelity, smoothness and efficiency in phenological estimation. Int. J. Appl. Earth Obs. Geoinf. 2016, 47, pp. 91–101.

- Jonsson, P.; Eklundh, L. (2002). Seasonality extraction by function fitting to time-series of satellite sensor data. IEEE Trans. Geosci. Remote Sens. 2002, 40, pp. 1824–1832.

- Zhang, X.; Friedl, M.A.; Schaaf, C.B.; Strahler, A.H.; Hodges, J.C.F.; Gao, F.; Reed, B.C.; Huete, A.(2003). Monitoring vegetation phenology using MODIS. Remote Sens. Environ. 2003, 84, pp. 471–475.
- Savitzky, A.; Golay, M.J.E. (1964). "Smoothing and Differentiation of Data by Simplified Least Squares Procedures". Analytical Chemistry. 36 (8): 1627–39. doi:10.1021/ac60214a047.

- Savitzky, Abraham (1989). "A Historic Collaboration".Analytical Chemistry. 61 (15): 921A–3A. doi:10.1021/ac00190a744.]

- Hird, J.N.; McDermid, G.J. (2009). Noise reduction of NDVI time series: An empirical comparison of selected techniques. Remote Sens. Environ. 2009, 113, pp. 248–258.

- Atkinson, P.M.; Jeganathan, C.; Dash, J.; Atzberger, C. (2012). Inter-comparison of four models for smoothing satellite sensor time-series data to estimate vegetation phenology. Remote Sens. Environ. 2012, 123, pp. 400–417.

- Kandasamy, S.; Baret, F.; Verger, A.; Neveux, P.; Weiss, M. (2013). A comparison of methods for smoothing and gap filling time series of remote sensing observations-Application to MODIS LAI products. Biogeosciences 2013, 10, pp. 4055–4071.

- Kandasamy, S.; Fernandes, R. (2015). An approach for evaluating the impact of gaps and measurement errors on satellite land surface phenology algorithms: Application to 20 year NOAA AVHRR data over Canada. Remote Sens. Environ. 2015, 164, pp. 114–129.

- Geng, L.; Ma, M.; Wang, X.; Yu, W.; Jia, S.; Wang, H. (2014). Comparison of eight techniques for reconstructing multi-satellite sensor time-series NDVI data sets in the Heihe river basin, China. Remote Sens. 2014, 6, pp. 2024–2049.

- Zhou, J.; Jia, L.; Menenti, M.; Gorte, B,(2016). On the performance of remote sensing time series reconstruction methods-A spatial comparison. Remote Sens. Environ. 2016, 187, pp. 367–384.

- Hinton, G. E.;Osindero, S. and Teh, Y., (2006). A fast learning algorithm for deep belief nets Neural Computation, 2006 18, pp. 1527-1554.

- YoshuaBengio, Pascal Lamblin, Dan Popovici and Hugo Larochelle (2006). Greedy Layer-Wise Training of Deep Networks, in J. Platt et al. (Eds), Advances in Neural Information Processing Systems, 2007, 19, pp. 153-160.

- Marc'AurelioRanzato, Christopher Poultney, Sumit Chopra and YannLeCun(2007). Efficient Learning of Sparse Representations with an Energy-Based Model, in J. Platt et al. (Eds), Advances in Neural Information Processing Systems, 2007, 19 pp. 1137-1144.

- Zeng, Z.; Lei, L.; Hou,S.; Ru, F.; Guan, X.; Zhang, B. (2014). A regional gap-filling method based on spatiotemporal variogram model of CO2 columns. IEEE Trans. Geosci. Remote Sens.2014,. 52,pp. 3594–3603.
- Michael Kwok-Po Ng; Qiangqiang Yuan; Li Yan; Jing Sun.(2017).An Adaptive Weighted Tensor Completion Method for the Recovery of Remote Sensing Images With Missing Data**.** IEEE Trans. Geosci. Remote Sens.2017, 55,pp. 3367-3381.
-
- Qiang Zhang; Qiangqiang Yuan; Chao Zeng ;XinghuaLi;Yancong, W. (2018)Missing Data Reconstruction in Remote Sensing Image With a Unified Spatial–Temporal–Spectral Deep Convolutional Neural Network**.** IEEE Trans. Geosci. Remote Sens.2018, 56,pp. 4274-4288.
-

- Henderson,Peter; Islam, Riashat; Bachman, Philip; Pineau, Joelle; Precup, Doina; Meger, David. (2017). Deep Reinforcement Learning that Matters. Technical report, McGill University and Microsoft Maluuba, 2017.
-
- L'Heureux, Alexandra; Grolinger, Katarina; Hany F. Elyamany; Miriam A. M. Capretz. (2017). Machine Learning With Big Data: Challenges and Approaches. IEEE Access 2017,5, pp. 7776-7797
- Bottou, Leon; Frank E. Curtisy; Nocedalz, Jorge. (2018). Optimization Methods for Large Scale Machine Learning. SIAM Rev., 2018,60(2), pp. 223–311.
- Arpteg, Anders; BjörnBrinne; Bosch, Jan; Crnkovic-Friis, Luka.(2018). Software Engineering Challenges of Deep Learning. 44th Euromicro Conference on Software Engineering and Advanced Applications, Sep 2018.
- Gerard Wolff, James.(2016). The SP Theory of Intelligence: Distinctive Features and Advantages. IEEE Access, 2016,4.
- JuergenSchmidhuber.(2015). Deep Learning in Neural Networks: An Overview. Neural Networks, Jan 2015, Vol 61, pp 85-117.
- Hornik. K; Stinchcombe, M; White,H. (1989). Multilayer feedforward networks are universal approximators. Neural Networks, 1989, Vol 2, pp 359-366.
- Simard, P; Bottou, L; Haffner,P; LeCun,Y. (1999). Boxlets: a fast convolution algorithm for neural networks and signal processing, Advances in Neural Information Processing Systems (NIPS 1998), 11, MIT Press, 1999.
- SutskeverIlya, I; Martens, J; Hinton, G. (2011). Generating Text with Recurrent Neural Networks. Proceedings of the 28th International Conference on Machine Learning, 2011.
- Schmidt, U; Roth, S. (2014). Shrinkage Fields for Effective Image Restoration. IEEE Conf. on Computer Vision and Pattern Recognition (CVPR), June 2014.
- Ulyanov, D;Vedaldi, A; Lempitsky, V.(2018). Deep Image Prior. Computer Science, April 2018.
- Bengio Y.(2007). Greedy layer-wise training of deep networks. Advances in neural information processing systems. January 2007.